Macroeconomic Factors *Do* Influence Aggregate Stock Returns

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Stock market returns are significantly correlated with inflation and money growth. The impact of real macroeconomic variables on aggregate equity returns has been difficult to establish, perhaps because their effects are neither linear nor time invariant. We estimate a GARCH model of daily equity returns, where realized returns and their conditional volatility depend on 17 macro series' announcements. We find six candidates for priced factors: three nominal (*CPI*, *PPI*, and a *Monetary Aggregate*) and three real (*Balance of Trade*, *Employment Report*, and *Housing Starts*). Popular measures of overall economic activity, such as *Industrial Production* or *GNP* are not represented.

The hypothesis that macroeconomic developments exert important effects on equity returns has strong intuitive appeal but little empirical support. In multifactor asset pricing models, any variable that affects the future investment opportunity set or the level of consumption (given wealth) could be a priced factor in equilibrium [Merton (1973), Breeden (1979)]. Securities affected by such undiversifiable risk factors should then earn risk premia in a risk-averse economy [Ross (1976)]. Macroeconomic variables are excellent candidates for these extramarket risk factors, because macro changes simultaneously affect many firms' cash flows and may influence the risk-adjusted discount rate. Economic conditions may also influence the number and types of real investment opportunities available.

Beginning with Chen, Roll, and Ross (1986), many articles have tried to show reliable associations between macroeconomic variables and security returns. To date, the literature has documented that aggregate stock returns are negatively related to *inflation* and to *money growth* [Bodie (1976), Fama (1981), Geske and Roll (1983), Pearce and Roley (1983, 1985)]. The impact of *real sector* macro variables on equity returns has been much more difficult

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to establish. Indeed, the following assessment of the asset pricing literature seems as pertinent today as it was in 1986:

> A rather embarrassing gap exists between the theoretically exclusive importance of systematic "state variables" and our complete ignorance of their identity. The comovements of asset prices suggest the presence of underlying exogenous influences, but we have not yet determined which economic variables, if any, are responsible. [Chen, Roll, and Ross (1986:383–384)]

Chan, Karceski, and Lakonishok (1998:175) dismiss the empirical relevance of macroeconomic factors to equity returns:

> The macroeconomic factors generally make a poor showing. Put more bluntly, in most cases, they are as useful as a randomly generated series of numbers in picking up return covariation. We are at a loss to explain this poor performance.

We extend previous research by estimating a GARCH model of daily equity returns in which both realized returns and their conditional volatility are allowed to vary with 17 macroeconomic series' announcements. Previous articles generally sought *time-invariant* effects of macro innovations on equity returns. However, if the impact of a specific macroeconomic development varies with the economy's condition, these tests have low power and are unlikely to find significant effects. Nonetheless, economically important announcements will be associated with returns unusually large in *absolute value*, even if the impact of macroeconomic news is time varying [Castanias (1979), Ross (1989)]. Therefore we may be able to document the *existence* of these events of unknown strength and direction if we model their *occurrence* in the conditional variance of returns.

We believe that our data on 17 macro announcement series from 1980 to 1996 constitutes the most extensive announcement dataset ever evaluated in this literature. From these announcements we identify three nominal variables (*CPI*, *PPI*, and *Monetary Aggregate—M1* or *M2*) and three real variables (*Employment Report*, *Balance of Trade*, and *Housing Starts*) as strong candidates for risk factors. Only the money supply affects both the level and volatility of equity returns. Beyond the money supply, the two nominal variables affect only the level of returns, while the three real macro variables affect only their conditional volatility. As an independent check on our conclusions, we investigate whether our identified macro factor candidates are associated with higher trading volume, as they should be if the macro announcements provide important news to the markets. We find increased trading volume associated only with the six macro series identified in the returns model.

Popular aggregate economic indicators such as *Industrial Production*, *Personal Income*, and *Sales* do not significantly affect returns, conditional return volatility, or trading volume. *Real GNP* surprises are associated with significantly *lower* conditional return volatility and have no effect on trading volume.

We subject our results to a series of robustness tests: we (i) separate the sample into three economic "regimes" defined according to the level of economic activity, (ii) estimate simultaneously the model for three contiguous subperiods, and (iii) use six instruments, one at a time, to model directly nonlinearities in the coefficients. The six announcement variables significantly affect equity returns in all the model variations. Although we do not investigate whether these six factor candidates are actually priced in capital market equilibrium, they seem to offer a good place to continue the search for priced factors.

Following a brief literature review in Section 1, Section 2 describes the GARCH model and the estimation techniques we use. The data are described in Section 3. The main results on macro risk factors are presented in Section 4, along with a robustness analysis. In Section 5 we confirm our findings by analyzing the impact of macro announcements on equity trading volume. The article concludes with a summary and discussion of the implications for future research.

1. Literature Review

Bodie (1976), Fama (1981), Geske and Roll (1983), and Pearce and Roley (1983, 1985) document a negative impact of inflation and money growth on equity values. Other variables are examined by Chan, Chen, and Hsieh (1985), Chen, Roll, and Ross (1986; henceforth CRR), Chen (1991), and Ferson and Harvey (1991). CRR identify five potential factors: the growth rate of *Industrial Production, Expected Inflation*, *Unexpected Inflation*, a bond *Default Risk Premium*, and a *Term Structure Spread*. They conclude that the default and term premia are priced risk factors, that *Industrial Production* is a strong candidate for being a risk factor, and that weaker evidence supports *Inflation*'s claim to that status. Shanken and Weinstein (1990) show that CRR's main conclusions depend on the specific method used to form test portfolios. Correcting some of CRR's standard error estimates for errors in variables further reduces the statistical importance of macro factors for equity returns. Lamont (2000) seeks to identify priced macro factors by determining whether a portfolio constructed to "track" the future path of a macro series earns positive abnormal returns. He concludes that portfolios that track the growth rates of *Industrial Production*, *Consumption*, and *Labor Income* earn abnormal positive returns, while the portfolio that tracks the *CPI* does not.

Cutler, Poterba, and Summers (1989) (hereafter CPS) find that *Industrial Production* growth is significantly positively correlated with real stock returns over the period 1926–1986, but *not* in the 1946–1985 subperiod, which substantially overlaps CRR's 1958–1984 sample period. CPS provide no support for the hypotheses that *Inflation*, *Money Supply*, and long-term *Interest Rates* reliably affect stock returns. More generally, CPS seek economic news events that might explain large stock market returns ex post. Like Roll (1988), they can account for only a very small proportion of total market variability, even using events that were observed after the stock market had reacted.

McQueen and Roley (1993) attribute the failure to identify significant macro factors to a shortcoming of the constant-coefficient models being estimated. They suggest that a given announcement surprise may have different implications at different points in the business cycle. For example, an increase in employment might be a bullish sign as the economy emerges from recession, but a bearish sign near a cyclical peak. They estimate a model in which each series' effect depends on overall economic conditions, defined according to the monthly growth rate of *Industrial Production*. They find that only two of their eight announcement series significantly affect the S&P 500 portfolio in a constant-coefficient model, but six carry significant coefficients in at least one of the economic regimes.[1] Boyd, Jagannathan, and Hu (2001) also find that macro news has distinctly time-varying effects on equity returns. They examine the impact of unemployment announcement surprises on the S&P 500 return over 1948–1995, and conclude that surprisingly high unemployment *raises* stock prices during an economic expansion but *lowers* stock value during a contraction. They hypothesize that higher unemployment predicts both lower interest rates and lower corporate profits, and conclude that the relative importance of these two effects vary over the business cycle.

Since our methodology involves volatility changes, we review studies that investigate whether macro variables affect equity return volatility. Except for a brief discussion in Andersen (1996), we found no previous research into the impact of macro *announcements* on market return volatility. However, some articles report a connection between equity return volatility and macroeconomic *conditions*. Hamilton and Susmel (1994) and Sinha (1996) estimate GARCH models of monthly U.S. equity returns in which the probability of switching from a high- to a low-volatility regime depends on broad economic conditions. They conclude that macro conditions significantly affect equity returns, in the sense that equity volatility is more likely to become (remain) high during a recession. Errunza and Hogan (1998) estimate VAR models for European stock returns for 1959–1993. They conclude that *Money Supply* volatility Granger causes equity volatility in Germany and France, and that the volatility of *Industrial Production* Granger causes equity volatility in Italy and the Netherlands. They find no evidence that past macro variables affect equity returns in the United Kingdom, Switzerland, Belgium, or the United States.

[1] When we replicate their analysis, we find that the specific results vary considerably across alternative definitions of the economy's condition. While it appears that time variation is an important issue, imposing a specific structure on time variation remains problematic.

Using a very different methodology, Schwert (1989) tests whether the volatility of inflation, monetary growth, or real economic variables can explain the time-variation in monthly return volatilities over 1859–1987. Instead of finding that greater macro volatility causes less stable financial returns, he finds it more likely that "financial asset volatility helps to predict future macroeconomic volatility" [Schwert (1989:1145)]. Fama (1990) makes a similar argument: because equity prices reflect expected future cash flows, equity price changes should predict future macro conditions.

2. Model Specification and Estimation

Multifactor asset pricing models apply when an investor's wealth does not completely describe her welfare. In a multiperiod asset pricing model, for example, investors demand positive returns for exposure to two broad types of risk: uncertain security returns during the *current* period, and possible changes in *future* investment opportunities [Merton (1973:876)]. Accordingly, any economic variable whose movements are correlated with the marginal utility of consumption is a potential priced factor in equilibrium. The intuition that macroeconomic conditions cause, or at least proxy for, changes in the investment opportunity set is appealing. For example, a change in the unemployment rate provides new information about future returns to human capital, an inflation surprise may change the expected return differentials between different asset types, and a change in the balance of trade may imply pending changes in the currency's exchange rate.

This article's analytical approach is informed by past, unsuccessful efforts to document reliable, time-invariant effects of macroeconomic conditions on equity prices. Previous studies of return sensitivity to macroeconomic variables regress monthly market returns on statistical innovations in the macro variables. In the simplest, single-factor case, researchers regress the market's return (r_t) on a potential factor's (Z) "surprises," $z_t \equiv Z_t - E_{t-1}(Z_t)$:

$$r_t = E_{t-1}(r_t) + \beta z_t + u_t. \tag{1}$$

A statistically significant estimate of the coefficient β indicates a reliable relationship between the factor and the market portfolio's value.[2] This methodology has been remarkably unsuccessful in detecting robust effects on aggregate equity market returns.[3]

[2] Although the market's sensitivity to Z makes this variable a factor candidate, further analysis is required to assess whether exposure to Z is actually priced in equilibrium.

[3] In contrast, researchers have readily detected significant macro announcement effects on Treasury yields [Balduzzi, Elton, and Green (1999), Fleming and Remolona (1999), Urich and Wachtel (1981), Cornell (1983), Hardouvelis (1984, 1987), Hardouvelis and Frankel (1985), Siegel (1985), Dwyer and Hafer (1989), Cook and Korn (1991), and Jones, Lamont and Lumsdaine (1998)], and on foreign exchange rate volatilities [Ederington and Lee (1993, 1996)].

Regression models like Equation (1) could fail to detect the important macro effects on the market equity portfolio's value for several reasons. First, the measured "market portfolio" excludes important sources of wealth that are not traded or whose returns are not readily measured. A standard errors-in-variables effect could then bias the estimated β toward zero.

Second, monthly stock returns incorporate enormous amounts of information, which may make the impact of macroeconomic developments hard to detect. We use daily, rather than monthly, data, which permits us to identify exactly when investors learn the announced macro values. Assuming that these announcements provide an unusually large amount of new information about the macro variable, daily returns should reflect the variable's specific impact more clearly than monthly returns, which incorporate many more financial developments.

Third, noisy measures of the expected value ($E_{t-1}(Z_t)$) also tend to bias the estimated β toward zero. We follow others in using surveys of market participants' expectations to measure the surprise component of each government macro announcement. These expectations reflect information available to the markets only a short time before the announcement, providing more accurate assessments of the announcement's surprise component than statistical expectations (e.g., a VAR model).

Finally, applying a fixed-coefficient model like Equation (1) to estimate a coefficient that actually varies through time could cause substantial inference problems. To see this, rewrite the essential components of Equation (1) as

$$r_t = \beta_t z_t + u_t, \tag{2}$$

where β_t, z_t, and u_t are jointly independent, $u_t = h_t \varepsilon_t$, and $h_t^2 = h_0^2$. When β_t varies through time, its estimate in a fixed-coefficient model like Equation (2) will be approximately the mean of β, $\hat{\beta} = E(\beta_t)$. The estimated coefficients may therefore fail to identify a factor candidate whose effect switches sign and averages close to zero over time, or is occasionally important. Moreover, using a fixed-coefficient model to estimate time-varying coefficients on the announcement surprises causes the estimated residuals to be heteroscedastic.

To understand this induced heteroscedasticity, suppose the true model is Equation (2), but we cannot model the intertemporal variation in β_t. Then the estimated residuals are given by $\hat{u}_t = u_t + \lfloor \beta_t - \hat{\beta} \rfloor z_t$, and their variance is

$$\hat{\sigma}^2_{u,t} = \sigma^2_u + E_{t-1}\left[\left(\beta_t - \hat{\beta}\right)^2 z_t^2\right] + E_{t-1}\left[u_t\left(\beta_t - \hat{\beta}\right) z_t\right]. \tag{3}$$

When β_t, z_t, and u_t are jointly independent, $E_{t-1}[u_t(\beta_t - \hat{\beta})z_t] = 0$. Then, on days with no macro announcements, $z_t = 0$ and the residuals' variance reduces to σ^2_u. But on days when macro announcements are released, the residuals' variance will (weakly) exceed σ^2_u, since in general $\beta_t \neq \hat{\beta}$ and $z_t \neq 0$. Thus it seems likely that we can extract information about the effect of an announcement series by modifying the rudimentary conditional variance specification. In Equation (2), make $h_t^2 = h_0^2 + \lambda D_t$, where D_t is a dummy variable equal to unity on days when the macro announcement is made. A significant positive coefficient λ is consistent with the hypothesis that z_t has a significant but time-varying impact on equity returns. Since the date of the announcement is known with certainty, it is correct to interpret a positive λ as the market's rational, ex ante expectation of higher volatility on that variable's announcement days.

A GARCH model is designed to identify variations in the conditional volatility of residuals. Adding lagged conditioning variables and a set of calendar dummy variables to a standard GARCH (1, 1), the model to be estimated is

$$r_t = E_{t-1}(r_t) + \sum_{n=1}^{17} \beta_n [F_{nt} - E_{t-1}(F_{nt})] + u_t, \tag{4}$$

$$E_{t-1}(r_t) = r_0 + \Psi \mathbf{X}_{t-1} + \sum_{w=1}^{4} \omega_w DW_{wt} + \sum_{k=1}^{6} \lambda_k DJ_{kt}, \tag{5}$$

$$u_t \equiv h_t \varepsilon_t, \text{ where } \varepsilon_t \sim N(0, 1) \text{ and i.i.d.}, \tag{6}$$

$$h_t^2 = \left\{ h_0^2 + \rho_1 \frac{h_{t-1}^2}{\Gamma_{t-1}} + \theta_1 u_{t-1}^2 + \gamma_p JPRE_{t-1}^2 + \gamma_\tau TB3M_{t-1}^2 \right\} * \Gamma_t \tag{7}$$

$$\Gamma_t = \exp\left\{ \sum_{w=1}^{4} \phi_w DW_{wt} + \phi_r PRE_t + \phi_s POST_t + \sum_{n=1}^{17} f_n DF_{nt} \right\}, \tag{8}$$

where

r_t = the realized market return on day t,
$E_{t-1}(r_t)$ = the (possibly time-varying) expected return for day t,
F_{nt} = the true value of the nth risk factor, $n = 1, \ldots, N$,
β_n = the average sensitivity of the market return to unanticipated changes in the nth factor,
r_0 = a constant return,
$\mathbf{X}_{t-1}$ = a vector of conditioning variables,
h_t = the conditional standard deviation of the error term u_t.

The parameters $\beta_n, \omega_w, \lambda_k, f_n, \phi_w, \phi_r$, and ϕ_s have unrestricted signs, but $h_0, \rho_1, \theta_1, \gamma_p$, and γ_τ are constrained to be nonnegative. The remaining variables in Equations (4)–(8) are defined below.

The return generating function of Equation (4) is a multifactor representation that equates factor surprises with the "surprise" components of 17 macro announcement series. The market's expected return [Equation (5)] depends on a standard set of predetermined variables:

1. Six financial variables ($\mathbf{X}_{t-1}$) that previous research has shown to influence conditional expected returns. The first four of these are lagged one trading day: the three-month Treasury bill rate (*TB3M)*, the junk bond premium (*JPRE)*, the Treasury term structure premium (*TPRE)* [used by Fama (1990) and Schwert (1990), among many others], and the own stock return [Conrad and Kaul (1988), Fama (1991)]. The remaining two variables are lagged five trading days to avoid any spurious correlation with returns: the dividend-price ratio (*DIVPRI*) used by Fama and French (1989) and Fama (1990), and the log of the market portfolio's value (*LMV)*.
2. Dummy variables (DW_{wt}) for four of the five weekdays (Wednesday is the excluded day). Weekly patterns in stock returns and return volatility are well documented [Cross (1973), Gibbons and Hess (1981), French and Roll (1986), Flannery and Protopapadakis (1988)]. Some writers [e.g., Harvey and Huang (1991) for foreign exchange] attribute at least part of these weekly patterns to the incidence of macroeconomic announcements.
3. The "January effect" [Banz (1981), Keim (1983)] is captured by six dummy variables (DJ_k), which identify the last three days in December (*DEC28–30* in Table 3 below), the last trading day of the year (*DECLD*), and each of the first four weeks in January (*JAN1–JAN4*).[4]

For days with no macro announcements, the bracketed terms in Equation (7) specify that the conditional variance depends on an ARMA(1, 1) process and two lagged bond market variables.[5] Coefficient restrictions guarantee that this part of the conditional variance is positive. This term is then multiplied by Γ_t, a function of dummy variables:

PRE_t and $POST_t$ are equal to unity on trading days that immediately precede (PRE_t) and follow ($POST_t$) a holiday [see Ariel (1990)].

DF_n are zero-one dummy variables that correspond to the announcement dates of each of the 15 distinct macro series.[6]

[4] A similar set of "January" dummies is used by Gallant, Rossi, and Tauchen (1992).

[5] Other ARMA structures yielded similar results. See Section 4.1 below. We added $JPRE_{t-1}^2$ to the volatility equation because LM tests on a prior model's residuals showed that it is the only conditioning variable from Equation (5) that is significantly correlated with the normalized squared errors. We added $TPRE_{t-1}^2$ after a referee suggested that bond yields are often used to model time variation in volatility in term structure and option models.

[6] Equations (4) and (7) refer to 17 announcement types. However, we have no expectations data for one series (*CCRED*), and two pairs of series (*PINC* and *PCONS*, *EMPNF* and *UNEM*) are always announced simultaneously. Thus we estimate coefficients only for 16 surprises and 15 announcement dummies.

As in Andersen and Bollerslev (1997) and Jones, Lamont, and Lumsdaine (1998), we assume that scheduled macro announcements have a multiplicative effect on conditional variance.[7] The exponential form of Γ_t in Equation (7) ensures that the estimated conditional volatility will be positive, even though the signs of the dummy variable coefficients have no constraints. We also follow them in distinguishing between persistent volatility shocks and transitory volatility changes due to scheduled macro announcements, days of the week, and holidays. Dividing the lagged conditional variance (h_{t-1}^2) by Γ_{t-1} in Equation (7) prevents these fully anticipated events from affecting future volatility.[8]

The parameter estimates maximize the log of the normal density function,

$$\Lambda = -\sum_{t=1}^{T}\left\{\frac{1}{2}\ln 2\pi + \frac{1}{2}\ln h_t^2 + \left(\frac{u_t}{h_t}\right)^2\right\}. \tag{9}$$

We use a recursive procedure to maximize this likelihood function; we maximize Equation (9) with a prespecified h_t at the start, then iterate on h_t until convergence.[9] Convergence is achieved when the sum of squared differences between successive parameter vectors, $(\mathbf{B}^{n+1} - \mathbf{B}^n)'(\mathbf{B}^{n+1} - \mathbf{B}^n)$, is smaller than an arbitrarily small number (0.01).

All the estimates we present exclude 11 days associated with the crash of 1987 and the sharp market decline of October 1989. We omit these days to reduce the possible impact of influential outliers, because it seems extremely unlikely that any of the macro announcements we study caused those large fluctuations.

3. Data

Estimating the model requires financial market returns, the date and value of each macro announcement, and a measure of market expectations about the announced value.

3.1 Security returns

We use the daily (close-to-close) return to the value-weighted NYSE-AMEX-NASDAQ market index from the Center for Research in Security Prices (CRSP), from the beginning of January 1980 through year-end 1996. We

[7] We experimented with alternative specifications of the functional form in Equation (7), and found that the main results are insensitive to specification changes. Among the specifications we tried, Equations (4)–(8) consistently produced the highest likelihood values, and the estimation converged most readily.

[8] The principle is that volatility due to well-anticipated events need (should) not have persistent effects [Andersen (1996)]. See the discussion of Figure 1. Estimating the model without dividing h_{t-1} by Γ_{t-1} gives very similar results, but the specification we use has better convergence properties.

[9] Missing observations cause difficulties when estimating conditional volatilities with an AR structure. We follow general practice and use the sample variance for the few missing lagged conditional variances.

also obtain two of our conditioning variables, $\mathbf{X}_{t-1}$, from the CRSP files:

DIVPRI—the dividend-to-price ratio for the value-weighted portfolio of NASDAQ, NYSE, and AMEX stocks on CRSP.

LMV—the log of the combined market value of all NASDAQ, NYSE, and AMEX stocks on CRSP.

Other conditioning variables are computed from data in the Federal Reserve's H.15 release of daily interest rates:

TB3M—the (coupon-equivalent) yield to maturity for the three-month Treasury bill.

TPRE—the difference in the yields to maturity of the 10-year Treasury bond and the 3-month Treasury bill (TB3M).

JPRE—the difference in the yields to maturity between Moody's BAA and AAA seasoned corporate bond indices.

Holidays require some adjustments. First, lagged values for predetermined variables refer to *business* (stock market trading) days, rather than to *calendar* days. Thus neither holidays nor weekend days appear explicitly in our data. We account for calendar effects with dummy variables that identify preholiday and postholiday trading days, and four of the five weekdays. Second, stock and bond market holidays do not always coincide. We therefore have some valid equity return observations for which the lagged bond yields (*TB3M*, *TPRE*, and *JPRE*) are unavailable. Rather than lose these observations, we approximate each such missing bond yield with its immediate predecessor.

3.2 Macro series announcements

Federal government agencies regularly announce newly calculated values for economic variables. An announcement during month t reports the series' value in month $t-k$, where generally $k=1$. The schedule for these announcements is known well in advance, generally by the previous year-end.

Every week, MMS International (now a subsidiary of Standard & Poor's) collects money market economists' expectations for some of the series scheduled to be announced during the subsequent week. We chose to use announcement "surprises" based on market participant surveys rather than on econometric models, as in many previous studies, because we feel that survey expectations more accurately capture contemporary market sentiment. Moreover, most econometric estimates of macro series innovations utilize *revised* data series, which are unavailable to market participants on the announcement date. Our announcement data contain the values that were actually announced to the public. From the set of macro variables forecasted by MMS, we selected 17 series that, a priori, seemed most likely to influence U.S. security returns. Many of these announcements have been studied previously, and we incorporated one colleague's assertion that the market particularly "watches" the employment and housing reports. We purchased data on the 17 series' announcement dates, median survey expectations, and announced values for the period 1980–1996.[10]

The series and the mnemonic abbreviations by which we refer to them are listed in Table 1. The data for most series are complete from February 1980 through year-end 1996, but the expectations for a few series (*CONSTR*, *EMPNF*, *HOMESL*) begin later. There are no expectations for the consumer credit series (*CCRED*).[11] Table 1 also shows the time of day when each announcement occurs. Most series are announced early in the day, making it appropriate to match the announcement with that day's close-to-close equity return. However, the money supply (*M1* and *M2*) and, until October 1995, consumer credit (*CCRED*) are announced after the equity markets close. We "shift" these three announcements forward one trading day to align them with the returns they should affect. We also shift the few announcements that occur on stock market holidays, aligning them with the first subsequent business day's stock return.

Most of the macro series are naturally expressed as growth rates. For series that are reported in other units (e.g., dollars or number of units), we choose meaningful deflators with which to convert the announced values and their corresponding expectations to a monthly percentage change. Choosing a deflator for the two housing series (*HOMEST* and *HOMESL*) presented a challenge, since we have no data on the nation's stock of housing units. We construct a proxy for the number of housing units in place by assuming (somewhat arbitrarily) that housing units numbered 50 million at the start of 1980, and applying a 1.8% annual depreciation rate for housing.[12] Combining announced *HOMEST* values with depreciation then yields an estimated housing stock at each point in time, which we use to convert the announced number of housing starts (*HOMEST*) and home sales (*HOMESL*) into percentage growth rates. To convert the balance of trade (*BOT*) to a proportion, we deflate each month's deficit (measured in current dollars) by the sum of seasonally adjusted imports and exports in the preceding quarter.[13] The standard deviations of the various "announcement surprise" series vary quite substantially; we standardize each surprise series to have unit variance.

[10] MMS would not provide information about the dispersion of their forecasters' expectations. Despite our extensive dataset, there are many additional macro announcements for which we have no information.

[11] We collected announcement dates for these four series back to February 1980, using a set of annual announcement schedules provided by the Office of Management and Budget. Missing or uncertain announcement dates were identified via the Dow Jones News Retrieval System.

[12] This 1.8% reflects unpublished previous research by A. A. Protopapadakis. The Bureau of Economic Analysis depreciation rate for the current value of residential structures averages 1.55% over our sample period.

[13] The computation of *BOT* is further complicated by a change in the underlying concept for the announced series. Through October 1994, the announced "trade deficit" describes the balance of merchandise trade. Beginning in November 1994, the announced series describes the trade balance in goods and services. We modified the deflator series to reflect the change in the *BOT* series' coverage.

Table 1
Macroeconomic announcements[a]

Variable	First available data for: Ann. dates	First available data for: Expectations	Announcement time of day	Mean [*p*-value][b]	Sequence[c]
Balance of trade (*BOT*)	January 1980	February 1980	2:30 p.m. through 11/29/83 9:30 a.m.–12/29/83 8:30 a.m.–1/27/84 on	−0.0356 [.008]*	13.3 (9–15)
Consumer credit[d] (*CCRED*)	March 1980	Never available	4:15 p.m. through 3/15/84 4:00 p.m. though 10/6/95 3:00 p.m. thereafter	n.a.	14.2 (8–15)
Construction spending (*CONSTR*)	March 1980	April 1988	10:00 a.m. always	0.0968 [.038]*	12.5 (9–14)
Consumer price index (*CPI*)	February 1980	February 1980	9:00 a.m. until 3/23/82 8:30 a.m.–4/23/82 on	−0.0030 [.394]	7.8 (4–11)
Employment (nonfarm payroll) (*EMPNF*)	February 1980	February 1985	8:30 a.m. always	0.0016 [.407]	1.5 (1.5–2.5)
Unemployment (*UNEM*)	February 1980	February 1980	9:00 a.m. through 3/5/82 8:30 a.m.– 4/2/82 on	−0.0539 [.000]*	Same as EMPNF
New home sales (*HOMESL*)	March 1980	March 1988	10:00 a.m. always	0.2695	11.8
Housing starts (*HOMEST*)	March 1980	March 1980	2:30 p.m. through 11/17/83 9:30 a.m.–12/20/83 8:30 a.m.–1/18/84 on	[.248] 0.0015 [.116]	(9–14) 7.3 (5–9)
Industrial production (*INDP*)	February 1980	January 1980	9:30 a.m. through 10/16/85 9:15 a.m. thereafter	−0.0012 [.477]	5.8 (4–9)
Leading indicators (*LEADI*)	February 1980	February 1980	Before 2/29/84, various times between 8:30 and 10:30 a.m. From 3/29/84: 8:30 a.m.	0.0030 [.457]	12.0 (9.5–14)
M1 (weekly)	January 1980	January 1980	4:15 p.m. through 3/15/84 4:30 p.m. thereafter	0.0580 [.161]	n.a.
M2	June 1981	December 1981	4:15 p.m. through 3/15/84 4:30 p.m. thereafter	0.0009 [.469]	4.5 (1–9.5)
Personal consumption (*PCONS*)	February 1980	July 1985	10.00 a.m.	0.0383 [.007]*	9.1 (6–12.5)
Personal income (*PINC*)	February 1980	April 1981	10.00 a.m.	0.0268 [.078]	Same as PCONS
Producer price index (*PPI*)	February 1980	February 1980	8:30 a.m. always	−0.0848 [0.000]*	4.0 (1–8)

Table 1
(continued)

Variable	First available data for: Ann. dates	Expectations	Announcement time of day	Mean [p-value][b]	Sequence[c]
Real GNP and Real GDP[e] (*RGNP*) (quarterly)	September 1980	80-3 to 91-3 Since 91-4	10:00 a.m. through 10/20/83 8:30 a.m.–12/21/83 on 8:30 a.m. always	0.0054 [.132]	n.a.
Retail sales (*SALES*)	February 1980	February 1980	2:30 p.m. through 11/10/83 8:30 a.m.–12/13/83 on	−0.0484 [.188]	4.1 (3–8)

[a] Except for *M1*, series announcements occur monthly.

[b] This column reports the mean announcement surprises (the actual announced values less the median MMS forecasts), with a p-value (in brackets) for the hypothesis that the mean surprise equals zero. Values marked with an * differ significantly from zero at the 5% confidence level.

[c] The "sequence" of a variable is its place in the sequence of that month's announcements. We report the mean announcement sequence for each series and the range over the sample period. *M1* and *GNP* do not have sequence assignments because they are announced weekly and quarterly, respectively.

[d] MMS does not collect expectations information on *CCRED*.

[e] Announcements occur monthly about the most recent calendar *quarter's* rate of *GNP* or *GDP* growth. Through December 1985, these announcements were called the "flash" estimate (announced about 10 days before the quarter's end), the "first revision" (announced about 20 days after the quarter's end), and the "second revision" (announced one month after the first revision). After December 1985 there were no flash estimates, but rather a "preliminary" estimate (announced about 20 days after the quarter's end) and two further revisions.

Following prior researchers, we test whether the expectations data were unbiased over the full sample period, as one indication of the expectations' quality. The next-to-last column in Table 1 shows that we cannot reject the hypothesis that the mean announcement surprises are zero for most, but not all, of the macro series. In replicating McQueen and Roley's S&P 500 estimation results, we experimented with their adjustment to expectations [their note 8] that uses interest rate changes between the survey date and the announcement date to proxy for information reaching the market during that interval. We found that these adjustments did not affect the conclusions materially and decided to use the unadjusted MMS expectations for simplicity.

The order in which variables are announced varies each month. It is plausible that a variable's order of announcement modulates its impact on the equity market. We create a "sequence" variable for each announcement which contains that announcement's order for every month. For example, if *CPI* is the fifth announcement for month *N*, then its sequence is five for that month. The last column of Table 1 shows the average "sequence" of each macro announcement and its range.

Table 2, panel A shows the incidence of the 17 announcement series. At least one macro announcement occurs on 56% of the 4288 trading days in our sample. As many as five different series have been announced on the same day. The rightmost column of panel A shows that return volatility on announcement days generally exceeds the volatility of no-announcement days. The standard deviation of market returns tends to increase with the number of announcements, but this effect is not monotonic.

Table 2, panel B shows that each monthly macro series includes around 200 announcements, while the weekly *M1* series has 882 announcements.

Table 2
Macro announcement summary statistics

Panel A: Trading days by announcement status

	Number of days	% of days	St. dev. of *MKTVW*[a]
Number of trading days[b]	4288	100.0%	0.771
With no announcements	1887	44.0%	0.744
With announcements	2401	56.0%	0.791
One announcement	1477	34.4%	0.800
Two announcements	679	15.8%	0.751
Three announcements	159	3.7%	0.836
Four announcements	65	1.5%	0.935
Five announcements	21	0.5%	0.612

Panel B: Announcements by macro variable

Macro variables	No. of announcements	St. dev. of *MKTVW*[a]
Balance of trade	202	0.840
Consumer credit	199	0.860
Construction	201	0.827
CPI	202	0.738
Employment (nonfarm) and unemployment[c]	203	0.921
Home sales	199	0.656
Home starts	201	0.818
Industrial production	202	0.705
Leading indicators	202	0.706
M1	882	0.859
M2[d]	180	0.760
Personal consumption and personal income[e]	200	0.772
Producer price index	201	0.746
Real GNP[f]	201	0.613
Sales	202	0.743
All 2401 announcement days:	3677	

[a] The standard deviation of returns for the value-weighted market index (*MKTVW*) on the indicated set of days.

[b] We exclude from all the statistics and analysis 11 "crash days" that exhibit large price movements in October 1987 and October 1989 in order to avoid unreasonably influential observations.

[c] These two series are always announced simultaneously, but we have separate expectations data for each. We use the designation *EMP* to refer to an employment-related announcement, as opposed to the distinct expectations for nonfarm employment (*EMPNF*) or the unemployment rate (*UNEM*).

[d] *M1* is announced weekly, while *M2* is a monthly series. However, the monthly *M2* variable is always announced simultaneously with a weekly *M1* report.

[e] These two series are always announced simultaneously, although we have separate expectations data for each. We use the designation *CON* to refer to a consumption-related announcement, as opposed to the distinct expectations for personal consumption expenditures (*PCONS*) or personal income (*PINC*).

[f] Even though it is quarterly, *RGNP* has 201 announcements because the Bureau of Economic Analysis makes three monthly announcements about each quarter's *GNP* (see Table 1, note e).

The unemployment rate (*UNEM*) and the number of nonfarm employees (*EMPNF*) are always announced in the same report, as are personal consumption expenditures (*PCONS*) and personal income (*PINC*). Each of these announcement pairs shares one dummy variable, but we have a separate surprise measure for each series. Panel B of Table 2 also reports the return volatility for each type of announcement.[14] Though return volatility is generally higher on announcement days, the announcement day returns for

[14] This calculation counts *all* the returns associated with the announcements of each variable, even when multiple series announcements occur on the same day.

Home Sales, *Industrial Production*, *Leading Indicators*, and *Real GNP* exhibit lower volatility than no-announcement days. The lowest volatility is associated with *Real GNP* and the highest with the *Employment Report* (at 82% and 123.4% of the no-announcement volatility, respectively).

4. Identifying Risk Factors

Table 3 reports estimation results for the full sample period, January 2, 1980, to December 31, 1996. Coefficient estimates for the "Returns Equation (4)" for the β_n coefficients of the standardized announcement surprises. The numbers reported in the "Conditional Variance Equation (7)" column are $\exp\{f_n\}$ but the associated P-values refer to the hypothesis that $f_n = 0$. Thus a reported number greater (less) than unity indicates that the associated macro series increases (decreases) volatility relative to the volatility on a day with no macro announcements. Weekday (ω_w, ϕ_w) and holiday (ϕ_r, ϕ_s) coefficients are reported analogously.

Several of the lagged conditioning variables (*MKTVW*, *TB3M*, *TPRE*, and *DIVPRI*) have significant coefficients in the expected returns equation [Equation (5)], and their signs are consistent with previous research. The estimated ARMA structure (shown in the lower right portion of Table 3) is highly significant, the AR1 coefficient (ρ_1) is well below unity, and the MA term (θ_1) is small. The sum of the ARMA coefficients, $\rho_1 + \theta_1 = 0.952$, is also well below unity (an indication of nonstationarity), but because the standard error is 0.076, the hypothesis that this sum is unity cannot be rejected.

Three macro announcements significantly affect the realized returns in Equation (4): *CPI*, *PPI*, and *M1*. All three coefficients are negative, indicating that higher-than-anticipated inflation or *M1* depresses equity values, consistent with previous studies. A one standard deviation *CPI* surprise affects *MKTVW* about as much (−0.136) as a one standard deviation *PPI* surprise (−0.153), while a similar *M1* surprise has approximately half that effect (−0.063). None of the real sector series significantly affects the return levels.

The conditional variance [Equation (7)] includes four real macro series with significant coefficients: *BOT*, *EMP*, and *RGNP* at the 1% level, and *HOMEST* at the 10% level. The *EMP* announcement has by far the strongest effect (the announcement raises conditional volatility by 68.5%), and the effects of *BOT* and *HOMEST* exceed 15%. The volatility coefficient on *RGNP* indicates that market returns are significantly *less* volatile on announcement days, a point to which we return below. Two dimensions of the *Money Supply* also raise return volatility: the weekly *M1* coefficient is significant at the 5% level and the monthly *M2* at the 10% level. Only *M1* affects both realized returns and their volatility.

The first three joint hypothesis tests reported in the last panel of Table 3 indicate that the announcement coefficients as a group are highly significant in the returns equation, in the conditional variance equation, and jointly.

Table 3
Full-period estimation results[a]

	Returns Equation (4)	Conditional variance Equation (7)	Auxiliary variables, Expected Returns Equation (5)	
BOT	0.041	1.274*	*MKTVW(−1)*	0.138*
	[.471]	[.003]		[.000]
CCRED	n.a.	1.134	*TB3M(−1)*	−0.033*
		[.162]		[.001]
CONSTR	−0.046	1.002	*JPRE(−1)*	0.048
	[.350]	[.986]		[.347]
CPI	−0.136*	0.882	*TPRE(−1)*	−0.034*
	[.010]	[.204]		[.014]
EMPNF	−0.006	1.685*	*DIVPRI(−5)*	8.473*
	[.903]	[.000]		[.026]
UNEM	0.017	(Same)	*LMV(−5)*	0.026
	[.784]			[.741]
HOMESL	−0.025	0.900	*DEC28–30*	−0.021
	[.496]	[.182]		[.909]
HOMEST	0.052	1.153**	*DEC LD*	0.040
	[.359]	[.092]		[.739]
INDP	0.006	0.918	*JAN1*	0.009
	[.917]	[.438]		[.906]
LEADI	0.037	0.866	*JAN2*	−0.012
	[.466]	[.128]		[.863]
M1	−0.063*	1.334*	*JAN3*	−0.039
	[.021]	[.000]		[.656]
M2	0.079	1.254**	*JAN4*	0.097
	[.139]	[.064]		[.158]
PCONS	−0.012	1.034	r_0	−0.523
	[.772]	[.709]		[.781]
PINC	0.002	(Same)		
	[.972]			
PPI	−0.153*	0.935		
	[.001]	[.509]		
RGNP	−0.014	0.774*		
	[.778]	[.008]		
SALES	−0.065	1.028		
	[.187]	[.804]		
			Auxiliary parameters, Conditional Variance Equation (7)	
MON	−0.076*	1.190*	$TB3M^2(-1)$	0.002
	[.015]	[.006]		[.557]
TUES	−0.060*	1.157*	$JPRE^2(-1)$	0.003
	[.046]	[.017]		[.763]
THURS	−0.068*	1.164*	ρ_1	0.902*
	[.024]	[.009]		[.000]
FRI	−0.037	0.819*	θ_1	0.051*
	[.222]	[.024]		[.000]
PRE (holiday)	—	0.456*		
		[.000]		
POST (holiday)	—	1.713*		
		[.000]		

Joint significance tests

Null hypothesis	Wald test p-value
All announcement coefficients are jointly zero in the returns equation [Equation (4)]	0.0049*
All announcement coefficients are jointly zero in the conditional variance equation [Equation (8)]	0.0000*
All announcement coefficients are jointly zero	0.0000*
EMPNF and *UNEM* coefficients are jointly zero in the returns equation [Equation (4)]	0.9396
PCONS and *PINC* coefficients are jointly zero in the returns equation [Equation (4)]	0.9589

[a] These are results of estimating the GARCH model [Equations (4)–(8)] for 4280 daily returns on the value-weighted market portfolio. The coefficient estimates in the Conditional Variance column are reported as exp{*coeff*} so that a value of 1.00 implies no effect on the conditional volatility compared to a no-announcement day. Numbers in square brackets are p-values for the hypothesis that the entry equals zero in the returns equation [Equation (4)], or that *coeff* is zero in the variance equation [Equation (7)]. *, **Coefficients are statistically significant at the 5% and 10% level, respectively.

The last two test statistics evaluate two announcement pairs that always occur simultaneously (*EMPNF* with *UNEM*, and *PCONS* with *PINC*). It is possible that the insignificance of their individual surprise coefficients in Equation (4) reflects correlation between their surprises. These tests fail to reject the hypotheses that each pair of coefficients jointly equal zero. Apparently the series individual insignificance reflects irrelevance rather than high correlation.

The results in Table 3 suggest that six macro variables may constitute equity market risk factors. The evidence about *BOT* and *HOMEST*—both *real* variables—is new.[15] The three nominal series (*CPI, M1*, and *PPI*) have been previously identified as important for equities, bonds, and foreign exchange rates. *EMPNF* has previously been shown to affect bonds and foreign exchange rates [e.g., Ederington and Lee (1993, 1996), Jones, Lamont, and Lumsdaine (1998)], but not stocks. We find no monthly broad output measure that significantly affects aggregate stock returns, contradicting some earlier evidence that *Industrial Production* (for example) constitutes a risk factor candidate.

Some of the macro variable surprises—*CPI*, *HOMESL, INDP*, *LEADI, PPI*, and *RGNP*—are associated with *lower* return volatilities compared to no-announcement days. Only the *RGNP* effect is statistically significant (1% level). It is also economically large: *MKTVW's* conditional volatility is nearly 23% lower on days when *RGNP* is announced, compared to no-announcement days. This surprising finding is not an artifact of our statistical model. Table 2 reports that the unconditional volatility of returns for the *RGNP* announcement days is much lower than for no-announcement days, and it is the lowest for any of the announcements. A nonparametric (Kruskal–Wallis) test also indicates that the equity returns on *RGNP* announcement days are significantly less volatile than for a typical no-announcement day.[16] Our discussion related to Equation (3) shows that it is possible to have a *lower* overall conditional volatility on announcement days if the announcement, its time-varying coefficient, and the error term are negatively correlated. However, we do not have a convincing intuition about why this should be true. Furthermore, in

[15] McQueen and Roley (1993) find that the merchandise trade deficit (*MTD*) is significantly negatively related to the S&P 500 returns, but only during periods of "*high*" economic activity. Hardouvelis (1988) reports a significant positive impact of trade deficit surprises on some (but not all) of the stock indices he evaluates during 1979–1982, but not during his 1982–1984 time period.

[16] As described in Table 1, the *RGNP* dummy variable combines three types of announcements: an initial "preliminary" estimate (called the "flash estimate" through 1985) and two subsequent revisions. To check whether combining these types of announcements is warranted, we divide each series into two. One new pair of variables describes the *preliminary* announcements (*URGNP1* and *DRGNP1*), while the other pair combines the two subsequent revisions (*URGNP2* and *DRGNP2)*. When we reestimate the model, neither type of *RGNP* surprise is significant in the returns equation, and both announcement dummies reduce volatility. However, the coefficient on *DRGNP2* is very significantly below unity, while the coefficient on *DRGNP1* is not. Thus the *RGNP* revision announcements are responsible for the puzzlingly low return volatility manifested in the raw data and estimated in our GARCH model.

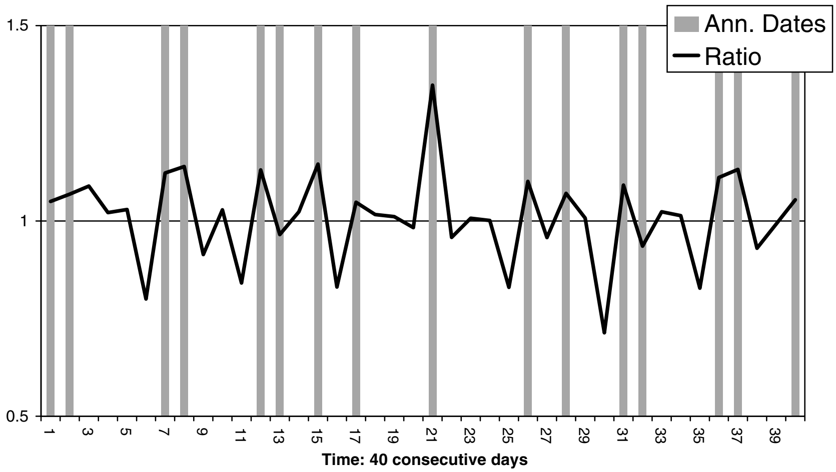

Figure 1
Estimated volatility of the full model divided by that of the "no-announcement" model

Section 5 we show that, unlike our other factor candidates, *RGNP* announcements are not associated with higher volume. Therefore we don't include *RGNP* among our factor candidates.

In order to assess the impact of macro announcements on the estimates of equity returns' conditional volatilities, we eliminate the macro surprises and their dummies from Equations (4) and (7) and reestimate the model. Figure 1 plots the ratio of our model's estimated volatility to the no-announcements model's for 40 typical observations early in the sample period. If the GARCH model's volatility estimates were not substantially affected by macro announcements, the ratio in Figure 1 should be approximately unity. Instead, we see that the two models' volatility estimates differ from one another by as much as 25%. The pattern of these differences shows how macro announcements affect the GARCH model's conditional volatility estimates. The lightly shaded bars in Figure 1 denote days on which a significant risk factor is announced. In our model, these announcements cause distinct, temporary increases in conditional volatility. For example, the *BOT* announcement scheduled for day 2 raises estimated volatility. On day 3, our model's estimated volatility falls back to its "normal" level. By contrast, the no-announcement model's ARMA process interprets the day 2's unusually large *BOT*-related return as an "error," and (incorrectly) carries its impact into the conditional volatility of subsequent days. Thus it misestimates both the day 2 and the subsequent conditional volatilities.[17]

Incorporating the effect of macro announcements permits the GARCH model to distinguish the macro announcements' transitory volatility from

[17] The largest spike in Figure 1 occurs on day 28, when *EMP*, *M1*, and *PPI* are announced together.

the more general volatility clustering. Ignoring the announcement information makes the standard GARCH model's conditional volatility estimates less variable. Without announcement variables in Equation (7), the estimated conditional volatility has a standard deviation of 0.275, compared to 0.285 for the model including the announcements. An F-test indicates that these standard deviations differ significantly (p-value $< .01$).[18]

4.1 Specification checks

We examine the extent to which the results in Table 3 might depend on the particular specification of Equations (4)–(8). We evaluate the robustness of our conclusions first by adding explanatory variables to the original specification and then by varying the basic regression model. In all cases, full results are available from the authors and the appendix provides further details.

The specification [Equations (4)–(8)] could plausibly include a variety of additional explanatory variables, such as leading and lagging values of the announcement surprises and their dummies, squared announcement surprises in the volatility equation [Equation (7)], an "in-mean" effect of conditional volatility in expected returns, and dummy variables to identify the 1980–1982 "Volcker" period of monetary control. Adding these and other explanatory variables did not change either our identified factor candidates or their significance levels from those in Table 3.

We also tried to model time variation in the surprise coefficients in an attempt to identify factor candidates directly from the return levels equation. An extensive literature documents that market betas and risk premia may covary with certain macroeconomic variables [e.g., Ferson (1989), Harvey (1989, 1991), Shanken (1990), Ferson and Harvey (1993), Ferson and Schadt (1996), Jagannathan and Wang (1996), Maroney and Protopapadakis (1999)]. The simplest specification of time variation is to estimate the model for three equal-sized, sequential subperiods. Coefficient estimates from these subperiods generally imply the same set of influential macro announcement series as those identified for the full sample period in Table 3. We also evaluate two types of time variation suggested by economic theory.

First, we replicate and expand the analysis of McQueen and Roley (1993), who find that market responses vary across their three economic "regimes." We alternately define economic regimes according to the growth rate of *Industrial Production* [as in McQueen and Roley (1993)], the *Unemployment Rate*, *Consumer Confidence*, and an index of *Job Openings*. We find that specific conclusions about factor candidates vary quite substantially with the definition of economic regimes. However, the six macro series identified

[18] R^2 statistics for the realized return equation [Equation (4)] provide an indication of the model's overall "fit." The full model's R^2 statistic is 0.037 (adjusted $R^2 = 0.029$) compared to 0.027 (adjusted $R^2 = 0.024$) for the same model without the announcements. OLS estimation of the returns equation [Equation (4)] that includes only the AR1 process gives an R^2 of 0.018.

in Table 3 are significant in at least one regime period, regardless of how we define regimes.

Finally, we model time variation in the surprise coefficients by allowing them to depend linearly on a set of predetermined macro variables, as in Ferson (1989), Ferson and Schadt (1996), and others. Very few of the new variables carry significant coefficients, which implies that time variation in these coefficients is not modeled well by this method. More importantly, neither the slope coefficients in Equation (4) nor the conditional volatility coefficients in Equation (7) change materially.

Overall, our conclusions proved very robust to a variety of specification changes. We are therefore quite confident that our identified factor candidates do not reflect some special feature of the estimated model.

4.2 The (un)importance of sequence

The question naturally arises whether the significant macro series in Table 3 are important in themselves, or because they convey new information that can be used to update forecasts about other aspects of the economic environment. Perhaps the market reacts the most to the first few announcements in any given month, and the least to the last few announcements, regardless of their identity.[19] Then, variables in Table 3 will be significant only if they are announced early each month, while later announcements would not be significant because they would add little to investors' macroeconomic assessments. We refer to this as the "sequence hypothesis."

Table 1 shows that the sequence of a series generally varies over time, and the series also vary in the uniformity of their sequences. For example, *Employment* consistently is among the first announcements for a given month, while *CPI*'s sequence ranges between 4 and 11. Early in the sample period, *CPI* announcements generally follow seven to nine other series announcements; later in the sample, *CPI* more typically ranks between 4 and 6.

To test the sequence hypothesis, we create an alternative set of surprise and dummy variables based on the announcement's sequence rather than on the macro series it describes. The new surprise variables ($USEQj$, $j = 1, 15$) contain the surprise components of the jth macro series announced for a particular month, regardless of that series identity.[20] Analogously, the new announcement dummy variables are *DSEQ1* to *DSEQ15*, where *DSEQj* equals unity on the day that the jth announcement is made for that month. Combining the announcements in this way does not introduce a new source

[19] Recall that all the *monthly* announcements in month N generally reveal information about month $N-1$. Thus, under this hypothesis, the first few announcements should reveal most of the macro information about month $N-1$.

[20] When two (or more) series are announced on the same day, there are two surprises to choose from for constructing the *USEQ* variable. We choose the surprise whose macro series is most significant in Table 3. We cannot rank the *M1* and *RGNP* announcements in the same fashion as we do the monthly series. Accordingly we include their surprise and announcement dummies separately.

of heteroscedasticity because each surprise's variance was already standardized to unity.

Under the sequence hypothesis, only the first few *SEQUENCE* variables should carry significant coefficients. This is not what we find. The sequence dummies 1, 6, 7, 9, 12, and 15 significantly increase return volatility at the 5% level, while only the 10th ranked surprise variable is significant in the returns equation [Equation (4)]. (Full estimation results are available from the authors.) Inconsistent with the sequence hypothesis, the variables announced *later* seem on average to be more important.[21] This result supports the hypothesis that investors are responding to the identity of the macro variables themselves rather than to the announcement sequence.

5. Macro Announcements and Trading Volume

Further evidence that the six announcements affect the market portfolio's value can be obtained by examining the impact of specific macro announcements on the equity market's trading volume (number of shares traded). It is well known that trading volume is positively correlated with equity price changes [Karpoff (1987), Harris and Raviv (1993)]. Beaver (1968) reports that an individual firm's trading volume increases by 34% during weeks when it announces quarterly earnings. Moreover, several information models [e.g., Kim and Verrecchia (1991), Blume, Easley and O'Hara (1994), Easley, Hvidkjaer, and O'Hara (2000)] show how investors' differing evaluations of new public information affect security prices through trading.[22]

We regress the log of daily equity trading volume on our macro series' announcement variables, the set of conditioning variables used in Equation (5), and some additional variables intended to capture persistence in volume:

$$\log(Volume_t) = \alpha_0 + \sum_{k=1}^{17} \theta_k \log(Volume_{t-k}) + \lambda MTKVW_{t-1} + \sum_{i=1}^{16} \beta_i [F_{nt} - E(F_{nt})]^2$$

[21] This result is foreshadowed in Table 3. For instance, the significant *UNEM* series is always (except once) announced first, and appears to be responsible for the significance of *DSEQ1*. *BOT* is generally announced last (and never earlier than 10th), which largely causes *DSEQ15* to be significant. *HOMEST*, which is significant at the 10% level, comprises the bulk of the statistically significant *DSEQ7*. On the other hand, *DSEQ4* and *DSEQ5* are insignificant because they are composed mainly of *SALES* and *INDP*, respectively, and both of those series are insignificant in Table 3.

[22] Although asset prices *could* change without significant trading volume, this would require that all market participants are equally risk averse, hold identical portfolios, simultaneously receive the same new information, and interpret news the same way. De facto, it seems that higher trading volume generally accompanies substantial price changes, as found (for example) by Fleming and Remolona (1999) and Balduzzi, Elton, and Green (1999) for the U.S. Treasury markets. Karpoff (1987) reviews the early part of this literature.

$$+\sum_{n=1}^{15}\delta_n DF_{nt}+\alpha_1 DNASD_t+\alpha_2 TIME_t+\gamma\mathbf{X}_{t-1}+\sum_{w=1}^{4}\Psi_w DW_{wt}$$

$$+\sum_{k=1}^{6}\Phi_k DJ_{kt}+\Phi_r PRE_t+\Phi_s POST_t+\varepsilon_t, \tag{10}$$

where,

Volume = the total trading volume in number of shares. Daily trading volume is available from CRSP for the NYSE and AMEX from the beginning of the sample until the end of 1994; daily NASDAQ volume is available starting in November 1982. Beginning in 1995, CRSP reports only the aggregate volume traded on all three exchanges. To construct a "total volume" series, we add together the disaggregated volume data through the end of 1994 and splice the resulting series with CRSP's aggregated, post-1994 volume data.[23]

DNASD = a dummy variable equal to unity after October 1982, when NASDAQ volume was first included in the volume series, and zero before.

TIME = a trend variable that is advanced by one each trading day.

$\mathbf{X}_{t-1}$ = the six conditioning variables included in Equation (5): the first lags of *MKTVW*, *TB3M*, *JPRE*, *TPRE*, and the fifth lags of *DIVPRI* and *LMV*.

The remaining variables are as defined for Equations (4)–(8).

We estimate Equation (10) as written above, and also in a restricted version that includes the announcement dummies (DF_n) but omits the squared surprises. The results reported in Table 4 strongly support our previous conclusions. In the "Announcement Dummies Only" regression, all the macro variables that significantly increase trading volume are the ones that significantly affect equity returns in Table 3. At the same time, the macro variables that do not affect returns do not increase volume significantly. Although *RGNP* has a significant announcement coefficient in Table 3, it *does not* increase trading volume, which is why we exclude it from the list of factor candidates. The results are similar in the regression that includes both the announcement dummies and the squared surprises.[24] In most cases, macro announcements influence volume in the same way as they influence returns in Table 3. When the announcement dummy is significant for stock volatility, it is also significant for volume, and when the surprise is significant for

[23] Estimating Equation (10) with the dependent variable specified as NYSE/AMEX volume or NASDAQ volume alone produces results very similar to those reported in Table 4.

[24] The only new feature of this specification is that *LEADI* surprises significantly increase volume. Recall that *LEADI* is not significant in Table 3, but it significantly affects return volatility in the "regime" results in Table A.1.

Table 4
Macro announcements and trading volume[a]

	Announcement dummies only	Announcement dummies and squared surprises	
Announcement variables	Dummy	Dummy	Squared surprise
BOT[b]	0.030*	0.032*	−0.003
	[.002]	[.003]	[.746]
CCRED	−0.001	−0.001	n.a.
	[.908]	[.870]	
CONSTR	0.010	0.008	0.002
	[.309]	[.419]	[.666]
CPI[c]	0.024*	0.017**	0.007**
	[.005]	[.077]	[.064]
EMPNF[b]	0.032*	0.026**	0.000
	[.010]	[.079]	[.934]
UNEM	same*	same**	0.006
			[.356]
HOMESL	−0.001	0.003	−0.003
	[.953]	[.728]	[.319]
HOMEST[b]	0.027*	0.026*	0.002
	[.002]	[.009]	[.681]
INDP	0.004	0.006	−0.002
	[.669]	[.535]	[.511]
LEADI	0.007	0.002	0.006*
	[.428]	[.837]	[.012]
M1[b, c]	0.071*	0.073*	−0.001
	[.000]	[.000]	[.710]
M2	0.027*	0.025**	0.001
	[.041]	[.064]	[.473]
CONS	−0.004	−0.008	0.002
	[.697]	[.525]	[.418]
PINC	same	same	0.002
			[.625]
PPI[c]	0.022*	0.015	0.006**
	[.025]	[.142]	[.085]
RGNP	0.004	0.004	0.001
	[.570]	[.600]	[.570]
SALES	−0.012	−0.013	0.001
	[.184]	[.219]	[.889]

[a] Estimation results for Equation (9), using OLS. The results in the column labeled "Announcement Dummies Only" come from a specification that excludes the announcements' squared surprises from the right-hand side. *, ** Coefficients are statistically significant at the 5% and 10% level, respectively. *P*-values are in brackets.

[b] The dummy significantly affects the conditional variance in Table 3.

[c] The surprise significantly affects the *MKTVW* return in Table 3.

stock returns, the squared surprise is significant for volume. The exceptions are *CPI*, where both the dummy and the squared surprise are significant (at the 10% level), and *M1*, where the squared surprises do not significantly affect trading volume.

6. Conclusion

Exposure to an economic variable that causes nondiversifiable risk for investors may be "priced" in asset market equilibrium. Although indicators of macroeconomic conditions seem good candidates for risk factors, previous studies have found only limited, and often contradictory, evidence that equity market returns respond to macro developments. Previous researchers have documented significant effects of *Inflation* and the *Money Supply* on equity returns, but evidence for other variables has been less compelling. In this article we seek to identify macroeconomic risk factor candidates by examining simultaneously the impact of macroeconomic announcements on level and conditional volatility of daily equity returns. We show that if the response of the market to announcement surprises is time varying, constant coefficient models will estimate only the average value of the time-varying coefficient, and the resulting residual estimates will be heteroscedastic. We use an appropriately specified GARCH model to detect such factors from the conditional variance. Therefore we identify as a potential "risk factor" any macro announcement series that *either* affects returns *or* increases the market's conditional volatility.

We use the most extensive dataset ever employed to study the impact of macro conditions on equity returns: 17 macro series announcements over the 1980–1996 period. We find that six of the 17 macro variables are strong risk factor candidates. Of these, two inflation measures (the *CPI* and the *PPI*) affect only the level of the market portfolio's returns. Three real factor candidates (*Balance of Trade*, *Employment/Unemployment*, and *Housing Starts*) affect only the returns' conditional volatility. A *Monetary Aggregate* (generally *M1*) affects both returns and conditional volatility. Some of these variables have been previously identified in the literature as possible equity market risk factors, but evidence on the importance of the *Balance of Trade*, *Employment*, and *Housing Starts* is new.

These risk factors consistently affect returns when we reestimate the model for numerous revisions to the basic specification, for three subperiods, for three distinct macroeconomic "regimes," and for a set of three size-based portfolios. The same factors also significantly increase stock market trading volume, while the other macro announcements do not. This provides independent confirmation of the factor candidates' importance to equity investors.

Remarkably, two popular measures of aggregate economic activity (*Real GNP* and *Industrial Production*) do not appear among our risk factors. Indeed, we find robust evidence that *Real GNP* announcements (in particular, the two revision announcements) are associated with lower rather than higher return volatility. *Industrial Production* exhibits a similar, though weaker, pattern. Neither macro announcement increases trading volume. Although we have no good explanation for this finding, it seems to imply that broad production measures do not generate systematic equity market risk.

The significance of our announcement variables in the conditional variance implies that previous tests of macro variables may have failed to detect significant effects because a constant-coefficient model of returns imposes too much structure on the data. Time-varying responses by the market or mismeasurement of the announcement surprises can make equity returns appear insensitive to macro announcements, even if the underlying macro series importantly affects prices. Unfortunately we have been unable to model explicitly time variation in the effects of macro announcements on returns.

Identifying macro variables that influence aggregate equity returns has two direct benefits. First, it may indicate hedging opportunities for investors. Second, if investors as a group are averse to fluctuations in these variables, these variables may constitute priced factors. A macro variable that reliably affects the value-weighted market portfolio's value need not be a priced factor, but it seems like a good place to search for such factors. Future research should investigate whether investors earn excess returns for bearing the risks associated with any of these factor candidates.

Appendix

A.1 Specification checks

Theory and past empirical work suggest additional variables that might be included in the returns equation: leads and lags of the announcement surprises, announcement dummies (possibly with their leads and lags), asymmetric responses to the announcement surprises, and *Pre*- and *Post*holiday dummies. Similarly, the volatility equation could plausibly include leads and lags of the announcement dummies, lagged, squared announcement surprises, squared conditioning variables, and lagged trading volume. Including all these variables in a GARCH model with 17 announcements would require estimating more than 250 coefficients. Such a model is unlikely to be estimated reliably. Therefore we adopt a more modest approach. We estimate the system [Equations (4)–(8)] for the full sample (as reported in Table 3), then regress the estimated residuals and their squared values on each set of possibly omitted variables listed above, one set at a time. While LM tests for each set separately reveal no distinct pattern of omitted variables, sporadic significant coefficients among the omitted explanatory variables suggest variables that might be significant if a more extensive model were estimated. We therefore estimate Equations (4)–(8) with the following specification:

(i) all the conditioning variables in Table 3,
(ii) all the announcement variables in Table 3 with a p-value less than .25, and,
(iii) all the potentially omitted variables from the above lists with a p-value less than .25 in the LM tests.

Few of the new variables carry significant coefficients in the full model. Most important for our purpose, neither the estimated coefficients of the macro announcements in Table 3 nor their significance is materially affected by the inclusion of these additional variables.

We experimented further with alternative model specifications:

1. *Including the conditional volatility term in the returns equation (MGARCH).* The MGARCH term in Equation (5) is statistically insignificant and of the wrong sign, and it has no important effect on the other coefficient estimates or their standard errors.[25]
2. *Adding expected announcement values to the returns equation.* When we include the expected values of the macro variables in the returns equation, we find that only the expected value of the *CPI* is significant at the 5% level. [Recall that Chen, Roll, and

[25] Scruggs (1998) notes that a negative coefficient on the conditional volatility's "in-mean" term is not an unusual result in the literature.

Ross (1986) concluded that expected inflation significantly affected equity returns.] The coefficients of "expected" macro variables are not significant as a group ($p = .26$). More importantly, none of our six factor candidates lose significance, and no other announcement becomes significant.

3. *More complete modeling of the January effect in the returns equation*. We reestimate the basic model by augmenting it with a separate dummy variable for each day in January. None of the individual day dummies are significant at the 5% level, and again we find no significant change in our "factor" conclusions.
4. *More elaborate ARMA specifications of conditional variance*. We experiment by adjusting the ARMA specification of the conditional variance. An AR(2) term is insignificant. For the AR(1) specification, we find several statistically significant MA terms with small coefficients. The alternative specifications have no substantial impact on the results; the main effect of the longer MA processes is to reduce substantially the value of the AR(1) parameter.
5. *Controlling for the Volcker monetary control period*. During the first few years of our sample period, the Federal Reserve explicitly targeted the growth rate of monetary aggregates. To determine if this subperiod is responsible for the significance of the monetary or inflation variables in Table 3, we create a "Volcker" dummy variable equal to unity from January 1, 1980, to November 1, 1982, and zero otherwise. We interact this dummy variable with the *M1*, *M2*, *CPI*, and *PPI* surprises in Equation (4) and their corresponding announcement dummies in Equation (7). None of the resulting dummy coefficients is significant at the 5% level.
6. *Removing the log(Market Value) variable*: *LMV* is generally included in empirical multifactor pricing models, but the series' nonstationarity may affect the values or the standard errors of the coefficient estimates. When we reestimate the full model without $LMV(-5)$, the coefficient values and their standard errors were effectively unchanged, except for the constant in the returns equation.

We also estimate the model for three size-based portfolios to see if the factor candidates we identify above show up with similar significance in at least some of these portfolios.[26] Even though there is no theoretical requirement that all risk factors are present in all such portfolios, it would be disturbing if the patterns of significance in these *SIZE* portfolios differ substantially from those of the market portfolio. We find that each of our risk factor candidates is significant in at least one of the three size-based portfolios, sometimes in all three. Only rarely is another announcement variable significant for one of the portfolios.

A.2 Variation across macroeconomic "regimes"

McQueen and Roley (1993) model possible time variation in the equity market's response to an announcement series by specifying distinct macroeconomic regimes. The critical issue is defining the "regimes." To start, we follow McQueen and Roley (1993) and use the deviations of *Industrial Production*'s growth rate from its trend to define three regimes. We estimate a monthly regression, $\ln(INDP_t) = a_0 + a_1 Time_t + e_t$, where $INDP_t$ is the level of *Industrial Production* in month t, and *Time* is a monthly trend. The estimated coefficient a_1 measures the average monthly *INDP* growth rate. The regime of *High* economic activity includes the months with the largest 25% of the residuals, the *Low* activity regime includes the months with the lowest 25% of the residuals, and the *Middle* regime includes the remaining 50% of the months. We then estimate an augmented version of the model [Equations (4)–(8)], in which each macro variable may have different coefficients in each of the three *INDP*-defined regimes. In order to save space,

[26] The *Large* portfolio includes the largest 10% of all firms traded on NYSE-AMEX-NASDAQ, the *Small* portfolio includes the smallest 10%, and the *Medium* portfolio included firms in the 45th–55th percentile of size. Complete results of the estimations are available from the authors.

Table A.1 reports only the coefficient estimates related to announcement variables. A chi-squared test on the model's log likelihood value strongly rejects the equality of all the coefficients across the three regimes ($p = .006$). When each announcement is considered separately, the hypothesis that the three subperiod coefficients are all equal is rejected in only a few instances (identified by asterisks in the "AE" columns of Table A.1). As in McQueen and Roley (1993), we find that macro information matters more in times of "high" economic activity. In Table A.1's *High* regime, seven announcements carry significant coefficients (at the 5% confidence level), while only one announcement is significant in each of the other two regimes.

The results in Table A.1 strongly support our initial assessment of macro factor candidates. Although no macro series is significant in all three regimes, all the risk factors identified in Table 3 are significant in at least one subperiod.[27] When a series' coefficient estimates differ across regimes, the variation is more frequently in the significance levels than in the coefficients' signs. A coefficient occasionally reverses its sign between regimes, but no announcement carries significant coefficients of opposite signs in different regimes. Finally, each significant macro series affects the same aspect of returns in Tables 3 and A.1. That is, if the series' announcement *surprises* are significant for the full sample, it is the *surprises* that are significant in one or more regimes. Conversely, if the announcement *dummies* are significant for the full sample, it is again they that are significant for at least one of the regimes. These findings show that this type of nonlinearity does not reduce the importance of the conditional variance dummies.

We replicated McQueen and Roley's analysis by defining the macro regimes in three alternative ways—according to the unemployment rate, an index of "help wanted" ads in major newspapers, and the University of Michigan Survey Research Center's Index of Consumer Sentiment. As shown in Table A.1, the six factor candidates from Table 3 are significant in at least some subperiods under all four regime definitions. However, alternate definitions of the same regime (e.g., "low" economic activity) do not always include the same significant macro announcements, and other announcement series (outside of our six factor candidates) are occasionally significant. Furthermore, the significant coefficients are not always concentrated in the "high" regime. (Complete results are available from the authors). Despite our failure to identify robust macro regimes, we find it encouraging that the influential macro series identified in Table A.1 (and under the other regimes) closely correspond to those identified in the full-period estimation results.

A.3 Nonlinear slope coefficients

Time variation is often modeled by specifying that the response coefficients depend on one or more predetermined economic variables. Ferson (1989), Ferson and Schadt (1996), and others present empirical evidence that the covariance between asset returns and consumers' marginal utility may depend on lagged economic conditions. We therefore tried to capture time variation in the announcement coefficients of the returns equation [the β_n in Equation (4)] by making them depend on several predetermined macroeconomic variables, one at a time. The return equation [Equation (4)] is modified to be $r_t = E_{t-1}(r_t) + \sum_{n=1}^{17}(\beta_{0n} + \beta_{1n}Z_{t-1})[F_{nt} - E_{t-1}(F_{nt})] + u_t$, where Z_{t-1} is the lagged value of an "instrument" variable, β_{0n} is the constant component of the nth factor's slope, and β_{1n} measures the impact of Z_{t-1} on the nth slope coefficient. The other model equations [Equations (5)–(8)] remain unchanged. We estimate this augmented model using each of our lagged auxiliary variables (*MKTVW*, *TB3M*, *JPRE*, *TPRE*, *DIVPRI*, and *LMV*) as the instrument for all the surprise coefficients. The results are very disappointing. Out of 90 total slope coefficients (15 β_{1n} coefficients in each of six regressions; one per instrument), only two differ significantly from zero; the *Employment* slope coefficients are significant when *TB3M* or *TPRE* are the instruments (at the 5% and the 10% levels, respectively). The estimates of β_{0n} are very similar to the coefficients of the initial model [Equation (4)]. In the volatility equation

[27] The only new significant variable is *LEADI*, whose conditional volatility is significantly *lower* (than on no-announcement days) during the *High* period.

Table A.1
Macro regime results[a]

	Returns [Equation (4)]					Conditional variances [Equation (7)]				
Period	High	Medium	Low	AE[b]	All 1/80–12/96	High	Medium	Low	AE[b]	All 1/80–12/96
BOT[c]	0.037	0.040	0.045		0.041	1.733*	0.925	1.345	**	1.274*
	[.793]	[.507]	[.750]		[.471]	[.005]	[.547]	[.215]		[.003]
CCRED	n.a.	n.a.	n.a.		n.a.	1.082	1.265	0.904		1.134
						[.705]	[.134]	[.583]		[.162]
CONSTR	−0.004	−0.070	−0.047		−0.046	1.084	0.976	0.904		1.002
	[.960]	[.381]	[.519]		[.350]	[.755]	[.883]	[.704]		[.986]
CPI[d]	−0.067	−0.091	−0.238*		−0.136*	1.214	0.944	0.846		0.882
	[.705]	[.221]	[.027]		[.010]	[.309]	[.703]	[.569]		[.204]
EMPNF[c]	−0.218	0.004	0.031		−0.006	2.398*	1.916*	0.698	*	1.685*
	[.162]	[.952]	[.735]		[.903]	[.000]	[.000]	[.162]		[.000]
UNEM	0.096	0.040	−0.112		0.017	(same)*	(same)*	(same)*		(same)*
	[.540]	[.650]	[.240]		[.784]					
HOMESL	0.049	−0.022	−0.052		−0.025	0.959	0.902	0.805		0.900
	[.454]	[.715]	[.461]		[.496]	[.857]	[.354]	[.400]		[.182]
HOMEST[d]	0.183	0.079	−0.162		0.052	1.031	1.135	1.344		1.153**
	[.227]	[.279]	[.281]		[.359]	[.910]	[.358]	[.104]		[.092]
INDP	−0.085	0.016	0.086		0.006	0.661	0.850	1.287		0.918
	[.297]	[.806]	[.644]		[.917]	[.141]	[.315]	[.401]		[.438]
LEADI	−0.168	0.033	0.149		0.037	0.580*	1.059	0.823	***	0.866
	[.149]	[.641]	[.283]		[.466]	[.025]	[.685]	[.451]		[.128]
M1[c,d]	−0.163*	−0.013	−0.078	***	−0.063*	1.317**	1.135	1.346**		1.334*
	[.001]	[.733]	[.150]		[.021]	[.055]	[.331]	[.061]		[.000]
M2	0.192*	0.084	−0.101		0.079	0.996	1.094	1.163		1.254**
	[.016]	[.340]	[.646]		[.139]	[.987]	[.663]	[.640]		[.064]
PCONS	0.135	−0.114	0.128	**	−0.012	0.973	1.018	0.933		1.034
	[.172]	[.108]	[.133]		[.772]	[.918]	[.901]	[.700]		[.709]
PINC	−0.062	0.064	0.001		0.002	(same)	(same)	(same)		(same)
	[.454]	[.455]	[.988]		[.972]					
PPI[d]	−0.332*	−0.083	−0.151	***	−0.153*	0.835	1.040	0.840		0.935
	[.000]	[.185]	[.128]		[.001]	[.486]	[.845]	[.397]		[.509]
RGNP	−0.095	0.008	−0.002		−0.014	0.866	0.828	0.598*		0.774*
	[.361]	[.919]	[.989]		[.778]	[.533]	[.159]	[.028]		[.008]
SALES	−0.165	0.010	−0.158		−0.065	0.726	1.064	1.255		1.028
	[.208]	[.866]	[.230]		[.187]	[.194]	[.704]	[.452]		[.804]

[a] Results of estimating the GARCH model [Equations (4)–(8)] for three subperiods constructed on the basis of the monthly growth rate in *Industrial Production*. The coefficient estimates in the "Conditional Variances [Equation (7)]" columns are reported as exp{*coeff*} so that a value of 1.00 implies no effect on the conditional volatility compared to a no-announcement day. Numbers in square brackets are p-values for the hypothesis that the entry equals zero in the returns equation [Equation (4)], or that the coefficient is zero in the variance equation [Equation (7)]. *, **Coefficients are statistically significant at the 5% and 10% level, respectively. Full period results (All 1/80–12/96) are reproduced for convenience.

[b] Indicated with *, **, or *** whether the joint hypothesis that the three coefficients are all equal is rejected at the 1%, 5%, or 10% level, respectively.

[c] The surprise significantly affects conditional variance in Table 3.

[d] The surprise significantly affects the *MKTVW* return in Table 3.

[Equation (7)], the coefficient estimates and p-values of the macro announcements (f_n) are virtually identical to those in Table 3.

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